CROP PRICE AND LAND USE CHANGE: FORECASTING RESPONSE OF MAJOR CROPS ACREAGE TO PRICE AND ECONOMIC VARIABLES IN NORTH DAKOTA

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

The objective of this study is to examine land use change for cropping systems in North Dakota. Using Seemingly Unrelated Regression with full information maximum likelihood estimation method, acreage forecasting models for barley, corn, oats, soybean, and wheat were developed to examine the extent to which farmers' expectations of prices and costs affect their crop choices.

The results of the study show that farmers' decision for acreage allocation is varied across the crops depending on how responsive they are to price, cost and yield of its own and competing crops. Substitutability and complementarity relationship of crops in the production have positive effect on crops selection when facing price, cost, and yield changes. In addition, the results revealed that expected prices have little effect on acreage response compared to expected costs and yield variables in most of the crop models.

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CHAPTER 1. INTRODUCTION

Background

Starting in the mid-1990s agricultural land use in North Dakota has experienced several rapid changes related to agricultural and energy policy. In addition, increased export demand for agricultural commodities in the livestock production sectors of developing countries is affecting how agricultural land is used in North Dakota. As prices change over the years due to these policy changes, crops that previously were not economically viable in much of North Dakota—especially corn and soybeans—have become competitive with the traditional small grains agriculture of the state, gaining a higher share of crop acreage. Figure 1 shows the change in acreage planted for the crops used in this study (barley, corn, oats, soybeans, and wheat) and composite others (sunflowers, flaxseed, canola, and sugar beet) from 1975 to 2014. By mid-2014, acreage used for corn, for example, had experienced a dramatic increase of 336% relative to that of 1995, with highest peak reached in 2013 at 3.85 million acres. Another crop showing substantial acreage increase is soybeans, which increased by about 809% during the same period. Wheat, on the other hand, shows a sharp decline from 12.68 million acres in 1996 to 7.57 million in 2014.

One may conclude that the rise in corn and soybeans price in recent years signals high profit for farmers. However, it may not always be true in the long run. Anecdotal evidence shows that high prices to some extent induce farmers to change their farming practices—e.g. switch from a crop rotation scheme to continuous cropping to take advantage of high crop prices. In doing so, farmers gain immediate short term profit, but in the long run, they may be worse off and suffer from profit loss due to reduced yield (Cai, Bergstrom, Mullen and Wetzstein, 2011). Moreover, as farmers switch from a crop rotation scheme to continuous cropping, soil fertility declines due to nutrient mining and it also reduces farmer's ability to use pest cycles, leading to increased need for pesticides (Cai et al, 2011). Continuous cropping can also increase soil acidification due to nitrate leaching, further reducing yield.

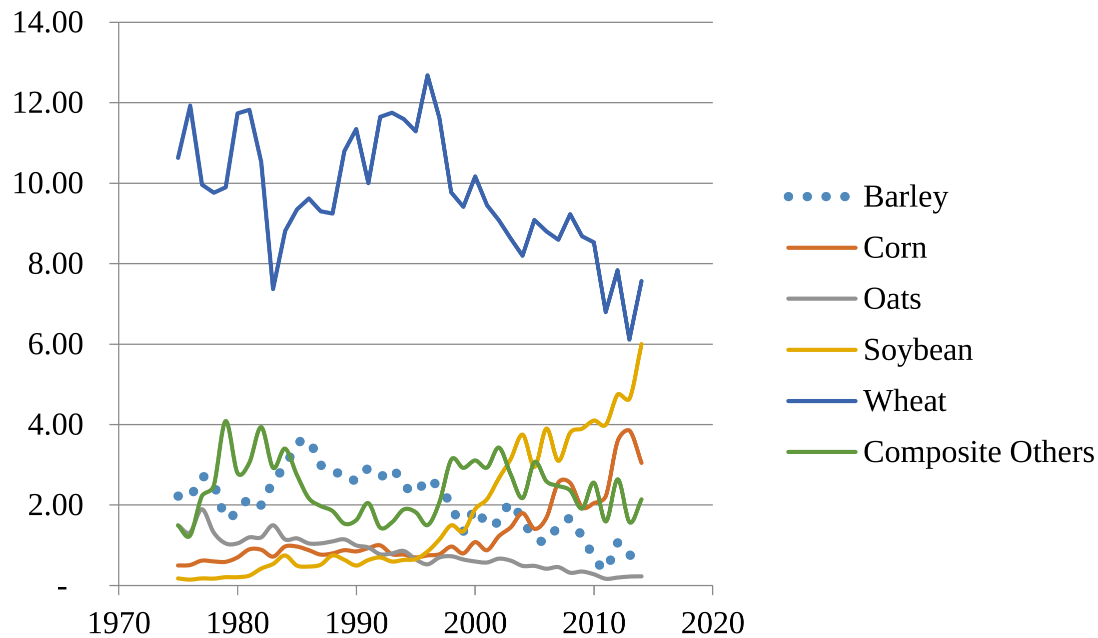

Figure 1. Acres planted for Barley, Corn, Oats, Soybeans, and Wheat, 1975 – 2014

Price volatility also leads to financial uncertainty for all competing crops, and thus impacts the entire local agribusiness industry, particularly those industries with crop-specific investments. Wheat has been the dominant crop in North Dakota, so expansion of corn acreage, for example, will affect the extensive infrastructure investments related to wheat cropping and distribution, if the infrastructure has only few alternative applications. As cited by Liang, Miller, Harri, and Coble (2011) in their study on acreage response of corn, cotton, and soybeans in southern U.S, found that the increase in corn acreage affected investments made in cotton because "machinery to harvest cotton is not useful for other crops, and post-harvest processing facilities such as gins are only capable of handling cotton" (Blaney, 2010). Similar to this finding, in the corn-wheat case, Haile, Kalkuhl, and Braun (2013), in their inter- and intra-annual global crop acreage response study, suggested that both the own and competing crop prices fluctuation were statistically significant and economically relevant to wheat acreage allocation and production. Instability in corn and soybeans prices affects wheat production and subsequent agribusinesses' investments in the wheat supply chain.

As reported by the USDA (2012), crops such as barley, oats and wheat—in contrast to corn and soybeans—have experienced a rapidly declining share of agricultural land. From 1995, the acreages of barley, oats, and wheat have decreased by 71%, 85% and 29%, respectively. Coupled with increasing input cost and prices, farmers often are faced with complex crop selection and acreage allocation decisions for their crops.

These policy and price changes have had (and will continue to have) impacts on farm profitability, as well as financial and environmental risks. Thus, modeling the impacts of policy and market variables on crop selection is of interest to policy makers, farmers, agribusiness investors, and other stakeholders. There have been many models developed; however, the majority of the previous research investigating changing crop acreage has been concentrated on corn and soybeans in response to the new energy policy. Crops such as oats and barley are often left out in the research, although they are partly substitute the margin in production and demand and thus often compete for the same land (Roberts & Schlenker, 2009). In addition to corn and soybeans, research related to other crops has been conducted, but these other crops have been mostly modeled as a function of own-price and other economic variables for specific states or nations. There are very few research on acreage response in North Dakota and currently they are limited to the effect of energy policy on the soybeans and corn acreage.

Problem statement

This research will consider the extent to which the expected crop price and cost affects North Dakota's corn, soybean, wheat, barley, and oat acreage. Crop farmers are believed to allocate their land to different crops based on the price and cost they expect from each crop, whether the differences of price and cost for each crop will provide them higher profit. Thus, the research question is: how strongly do expected prices of the five major crops of North Dakota affect farmers' crop allocation decisions from year to year? It is envisaged that this research is of current interest because of increased crop price volatility in recent years as well as increasing price trends.

Research objectives

The expected outcome of this research is a more specified and informed acreage response model that would assist farmers in their effort to increase production and profit in the long run. It is also envisaged that this research will increase understanding of how agricultural policy changes could affect other sectors in the economy in North Dakota.

Thesis overview

The models developed in this study are based on multivariate forecasting analysis on the supply of land using Seemingly Unrelated Regression with full information maximum likelihood estimation (SUR-MLE) method. The study focuses on forecasting acreage allocations for five crops—barley, corn, oats, soybeans, and wheat—in North Dakota. The data used for estimation are obtained from USDA National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) websites.

The content of this study is divided into five chapters. Chapter one explains the rationale behind this research and defines the problems that this research will answer. Chapter two will review the literature of existing acreage models in the past. Expected value of price, cost and yield are used in the equation models, thus this chapter also review how these expected values were measured in the past. The review also will analyze theoretical models that previous researchers have used as basis for their studies. Chapter three will provide the theoretical framework and the empirical models. It will explain in detail how the model is developed and applied. It will also explain briefly about the type and the source of the data used, how they were collected and utilized in the model development. Chapter four will explain the result of the estimation followed with a detailed discussion. The final chapter—chapter five—will conclude this thesis with a discussion of the implications of the research findings. It will provide some recommendations and suggestions for further research.

CHAPTER 2. LITERATURE REVIEW

Acreage response has been one of the important research areas in both agronomic and economic fields of study. A great number of models and forecasting techniques have been developed since the 1950s. These models have assisted greatly in applied policy analysis to examine the impact of certain policies on land use change and allocation. Policy makers often rely on these models to assist them in analyzing proposed new policies or reforming existing agricultural policies, leading to more informed agricultural policy implementation (Goodwin and Piggott, 2012).

Perhaps the earliest model ever developed was by Nerlove (1956), where he developed a general supply response function that was then applied by Askari and Cummings (1977) in their English-language survey two decades later. The model is one of the most successful in applied econometrics, as evidenced by various subsequent studies that referred to it (Colman, 1979; Muth, 1961; Binkley and McKinzie, 1984; Krakar and Paddock 1985; Bewley, Young, and Colman, 1987). While those studies were conducted following Nerlove's approach to specify a general supply response function, subsequent studies had broader scope and considered both producer and consumer economic behavior in a more theoretically consistent manner (Chavas and Holt, 1990; Lee and Helmberger, 1985; Lin, 1977; Lin and Dismukes, 2007). Studies post-Nerlove have developed various models for estimation from a single equation to multiple or a system of acreage supply equations (Bewley *et al*, 1987; Coyle, 1993; Barten and Vanloot 1996). In addition, explanatory variables selected for model estimation have differed across studies.

Despite the differences in variables used, most of the researchers and scholars agree that expected crop prices must be included as explanatory variables (Chavas and Holt, 1990; Krause and Koo, 1996; Choi and Helmberger, 1993; and Krause *et al*, 1996). However, consensus has not been reached regarding how the expected price is measured. In addition, the theoretical frameworks upon which previous researchers' models were based are also varied. The following section reviews 1) how expected crop prices have been measured in past research and 2) various theoretical frameworks that researchers have used in developing their crop acreage supply models.

Expected price

Agricultural producers make optimal crop acreage decisions and choices subject to output prices which are not known at the time when planting decisions are made. Thus, expected rather than observed output price are usually used for decision making. Studies on crop acreage response also take this into consideration. Many of the acreage response models developed in the past were specified as a function of the expected output price. Although there is general consensus on the importance of the expected output price in acreage response models, how expected price is measured is still somewhat varied.

Ryan and Abel (1973), in completion of Houck and Ryan's (1972) estimation of supply relationships for corn, sorghum, oats and barley after World War II, published an acreage response to prices and government programs using data from 1949-1971. Explanatory variables used in the model included acres for the crops (corn, oats, soybean, wheat and barley), barley acreage diversion payment rate, barley market price and oats market price received by farmers, average barley loan rate and average oats loan rate (both were weighted by acreage restriction requirements 1963-1965). In order to model the forecast, barley market price and oats market price were lagged. Following Houck and Subotnik (1969), and Houck and Ryan's (1972) approach, previous year's prices were utilized as proxy for expected market price. Their study showed that barley acreage is less responsive than oat acreage to changes in the price support variable, in absolute and in relative terms. A 10-cent-per-bushel increase in average barley loan rate (1963-1965) is associated with an increase of slightly less than one-half million acres in barley plantings.

Similar to Ryan and Abel's study, Krause and Koo (1996) developed a model for minor oilseeds in the Northern plains. Using the data from 1962-1993 they specifically evaluated wheat, barley, flaxseed and oilseed sunflower acreage responses to expected gross revenues, price risk and government program parameters. Expected gross is calculated by multiplying expected price and expected yield of the crops. The support prices for 1991-1993 were multiplied by 0.85, the "proportion of acres qualifying for deficiency payment in those periods" (Krause and Koo, 1996). In addition, all prices were deflated by the index of prices paid by farmers for production. They also included price variable risk, which was the "weighted variance of price received in the previous three years around the expected market price, and intercept shift after 1975" (Krause and Koo, 1996). Their study revealed that the expected revenue of flaxseed had a significant, positive effect on flaxseed acreage, whereas market price risk had no significant effect. Using the same approach as Houck and Subotnik (1969), and Houck and Ryan (1972), the expected market revenue is calculated by considering the past year's market price.

Following their previous work, Krause, Lee and Koo (1996) estimated acreage response to changes in price and government programs. Using Chembezi and Womack's definition of program and non-program wheat, they again evaluated the effect of price and risk but focused on the acreage response amongst regions and US as a whole. To model their acreage response, they consider, among other variables, not only wheat price and wheat support price but also a price risk variable. Their study suggests that the expected wheat price has a significant "negative effect on program complying acreage" while wheat support price has a "strong positive effect on nonprogram-planted acreage" (Krause *et al*, 1996). Program complying acreage is estimated to be affected positively by price risk; however, non-program-planted acreages were negatively affected by price risk. The study also showed that each region had different determinants for wheat acreage, and wheat producers in the central plains, southern plains, and other regions in the US are better off to increase their wheat acreage compared to northern plains.

Another investigation conducted by Liang, Miller, Harri, and Coble (2011) found similar results in regards to the effect of price and price risk on acreage responses in different regions. Their finding supports Krause, *et al* (1996) that each region had different determinants and elasticities for crop acreage responsiveness. In addition, they also agree with Just (1974) that price risk, measured by the variance of revenue, has a statistically significant effect on acreage response although the absolute magnitude of the effect is not large.

All these studies have followed Nerlovian tradition, where expected output price is determined from past market price and used as proxy for future price. Other studies, however, used futures prices in determining expected market price (Gardner, 1976; Peck, 1975; Telser, 1967; and Morzuck et al, 1980). They believed that futures price offers better prediction for expected market output price. Gardner explained that futures contract of certain year, reflects the market's estimate of that year's cash price.

Morzuck, Weaver and Helmberger's (1980) study of wheat acreage response utilized futures prices as a proxy for expected prices for wheat and competing crops. Their findings lend support for Gardner's thesis that futures prices could be considered as an alternative to using distributed lags in modeling price expectations. Their study also indicated that the relative price of wheat had a positive relationship with acreage planted for wheat. This is consistent with the results found by Krause *et al* (1996).

Choi and Helmberger (1993) estimated price elasticity for consumption demand, demands for stocks and acreage response of soybeans in the US. Their study questioned why previous researchers consider expected price as exogenous variable. To synthetize their argument, they consider futures price as proxy for expected market price. In addition to futures price, they also added demands for consumption and stock as their explanatory variables. In contrast to Gardner's suggestion, they found that expected price as measured by futures price should be considered as endogenous instead of exogenous variable. Their study supported Just and Rausser (1981) that futures prices forecast relatively well compared to other econometric forecast, and that acreage decisions could be based on the futures price.

While it seems futures price is good measure for expected price, Chavas, Pope and Kao (1983) cited in their study the mixed responses of the quality of forecast. For example, they cited Grossman and Stiglitz's (1980) and Bray's (1981) argument how unrealistic it is, under rational expectations, to assume that futures prices perfectly reflects all the information available in the market. Stein (1981, p.231) stated that "prior to four months to maturity, the futures price is biased and worthless estimate of the price at maturity." Thus, Chavas, Pope and Kao (1983) attempted to use both futures price and lagged cash price in the estimation. Their results questioned the efficiency of futures price as information for expected price, especially when government support programs are involved. But it does not necessarily mean that utilizing both lagged cash price and futures prices is the answer. Their study revealed high multicollinearity between the lagged cash price and the futures contract price, as both reflect similar market information. Their findings suggest that, futures price can only be a good estimator for expected price if government programs are not involved.

Despite the various ways expected market price has been interpreted, most research agreed that price factor plays a significant role in farmers' acreage allocation decisions. Farmers' decision is agreed to be affected by expected price. This work utilizes Vector Auto regression (VAR) lagged for two years. Variables such as price, cost, yield, and acres that affect each other are input in the VAR to forecast the expected prices.

Previous models and how they were developed in the past

Any economic model should be derived from a reliable theoretical framework (Chambers, 1988; Varian, 1978; Shumway, Saez, and Gottret, 1988). Thus far, there are various theoretical frameworks that have been introduced by economists and agriculture policymakers, ranging from strictly economic theory to more interdisciplinary models (Coyle, 1992; Arnade and Kelch, 2007; Holt and Moschini, 1992; Chavas and Holt, 1990; Duffy et al, 1994, Lee and Helmberger, 1985). The following discussion reviews the most commonly used frameworks in acreage response modelling.

One of the most used theoretical basis is the profit function from production theory (Lee and Hemlberger, 1985; Duffy et al, 1994; Chembezi and Womack, 1992). Lee and Helmberger first introduced the application of profit function in their study of price responsiveness of corn and soybeans in 1985. Their model has been cited and modified by other researchers for estimation of acreage response models. Arnade and Kelch (2007), for example, further modified the model to estimate area elasticity of crops. In estimating the elasticity they started off by specifying producer optimization decision to maximize profit subject to total sum of acres of land. From there, they introduced Langrangian multiplier to derive demand and elasticity functions. Although, the model is able to explain the elasticity, they explained that in contrast to ideal response equation, it is difficult to jointly estimate the system of supply and/or demand equation. To do so, may require imposition of “a set of extremely complex nonlinear cross-equation restrictions” (Arnade and Kelch, 2007).

In 1992, Chembezi and Womack studied the impact of farm programs on acreage response for corn in Cornbelt and Lake States, and wheat in Northern Plains under profit maximization. Their model maximizes expected profit for a crop producer subject to land availability under a) program requirement constraint and b) acres diverted under voluntary diversion constraint. Their study concluded that government program was successful in reducing corn and wheat planting. As far as the effect of expected price is concerned, their study revealed that expected market price for wheat has negative effect on program planted acres, but positive for nonprogram-planted acres.

Weersink, Cabas and Olale’s (2010) study on the effect of weather, yield, and price on crop acreage brought in new insight on how to treat price and yield in an acreage response model. While much of the research combined the effects of price and yield in their equation, Weesink et al (2010) suggested separating them. They argued that the effect of the distribution of climatic condition, to some extent, would affect yield and thus the acreage supply. Starting off with normal production function of profit maximizing crop producer, they calculated the expected yield and variance of yield. Their expected yield is calculated based on expected weather conditions, while the variance of yield is the weighted average of the squared deviations between actual and expected yield. Expected profit is the sum of expected revenue and covariance between crop price and yield minus the cost of production. Their study revealed that overall the length of the season, but not the intensity of the season, would increase crop yield. In addition, they also concluded that measuring acreage response should not exclusively focus on the effect of price and its impact on profitability. Yield should be taken into account separately to account for the effects of weather on profitability.

Another theoretical framework commonly used is expected utility function. When modelling acreage response with regards to risk, many researchers have applied an expected utility function to derive their model (Chavas and Holt, 1990; Krause and Koo, 1996; Adhikari, Paudel Houston and Bukenya, 2008; Liang et al, 2011). Chavas and Holt first developed this model from the Von Neumann Morgenstern utility function for assessing risk averse farmers' planting decision between corn and soybean. Subsequent research about the effects of risk on decision making has used or modified the model in their forecast. Coyle (1992), for example, applied it to linear mean-variance models and their dual, and Holt and Moschini (1992) used ARCH/GARCH (Autoregressive Conditional Heteroskedasticity) methods to represent variance in the utility model. In general this theoretical function includes gross revenue, variance of market prices (price risk), cost, and input levels as important explanatory variables. The decision problem of agriculture producer is to maximize utility subject to net revenue and the variance of market prices. With this model, the acreage response decision depends on how farmers' utility is expected to be affected by risks, including price and yield risks.

From the review, it is noted that the results of the estimations from previous research are varied. A wide range of models, variables and estimation methods have been applied in measuring acreage response. The variability of the estimation results supports Askari and Cummings' (1977) argument that estimation results will always differ due to the variation of models, theoretical framework that is used as basis for modelling, estimation method, differences in defining price and output measures, specification of sample period, variability of response parameters among regions, and variability of commodities in question.

Despite the abundant research and model development to forecast crop acreage, none of these models have specifically examined major crops in North Dakota, and none jointly estimate acreage response functions for major field crops that compete for the same land in one model. Crops such as wheat, barley, oats, corn and soybeans are partly substitute the margin in production and demand and thus compete for the same acres of land (Roberts & Schlenker, 2009). There are a few studies that have included North Dakota. For example, Krause and Koo (1996) and Krause, Lee and Koo (1995) included North Dakota as part of a regional study of the Northern Great Plains. Gustafson (2002) focused only on the corn acreage expansion due to ethanol production in Western North Dakota. Inclusion of all the competing crops in North Dakota is believed to be important due to the fact that acreage, supply and price of certain crops in the area affect crop selection decisions and acres allocation shared for other crops.

This work will differ from previous studies in that it focuses on estimating acreage response of various crops in North Dakota as functions of their own prices, yields, and costs, as well as those of competing crops. It emphasizes the need to estimate the extent to which a farmers' acreage response is altered by expected crop prices in North Dakota. In addition, it will also examine how much the price will affect farmers' acreage responses. In modeling the acreage response, this work will examine from supply analysis and farmers' expected profits for crops. Farmers' land allocation decisions are based on farmers' expected profits for each crop, which are based on their expected prices, costs, and yields. More on this will be discussed in the theoretical and empirical model section.

CHAPTER 3. MODEL DEVELOPMENT

This chapter develops acreage response models for barley, corns, oats, soybeans and wheat in North Dakota. The models are used to forecast the acres that agricultural producers will collectively allocate to each crop each year. These forecasting models include expected costs, expected prices, and expected yields for each crop as explanatory variables.

Theoretical framework

Consider the case of the individual farmer to determine how crop producers allocate their land, the model starts off with considering how crop producers make their decision with regards to acres allocation for each crop. A profit maximizing farmer's decision to allocate the acres is based on expected prices, yields and operating costs for each crop. Hence, the decision problem for a profit-maximizing multi-output farmer given a specific field and year is:

$$\max_{i} E[\pi_{ikt}(EP_{it}, EY_{ikt}, EC_{ikt})] \tag{1}$$

where π_{ikt} is the profit from crop *i* in field *k* in year *t*, which is a function of expected prices (EP_{it}), expected yields (EY_{ikt}) in the specified field, and the expected costs (EC_{ikt}). Note that crop yields and costs are assumed to vary by field due to climate, soil type, and constraints caused by rotational considerations. The above expression is a modified version of Lee and Helmberger's (1985) and Krause and Koo's (1996) decision problem for crop farmers. Regional crop coverage is the aggregation of individual farmers' decisions, and is thus a function of the same variables. For convenience, the *k* subscripts for fields can be dropped when modeling acreage in aggregate.

The volatility of agricultural commodity prices is well-known, and it results from inelastic supply and demand for these goods in conjunction with supply shocks attributable to weather. Farmers have relatively few opportunities to adjust their production mix in response to price signals—the primary occasion being at planting, though they also make management decisions that differentially affect crop yields throughout the growing season (Krause and Koo, 1996). Because commodity prices are volatile, acreage allocated to each crop within a region may vary significantly between consecutive years in response to producers' expectations about prices, yields, and production costs. Thus, the model of individual decisions in aggregate for a particular state can be represented as follows:

$$A_t = f\left(EP_t, EY_t, EC_t; \beta_p, \beta_y, \beta_c\right) + \varepsilon_t \tag{2}$$

where A_t is a *n* by 1 vector of acreages allocated to n crops in year *t*; EP_t, EY_t, and EC_t are 1 by *n* vectors of expected prices, yields, and operating costs, respectively, for *n* crops in year *t*; β_p, β_y, and β_c are time-invariant *n* by 1 vectors of coefficients relating the acreage of each of the *n* crops to the expected prices, yields, and operating costs of all *n* crops; and ε_t is a *n* by 1 vector of *correlated*[1] error terms for each of the n crops in year *t*.

Empirical model for acreage response

Following the theoretical model specified in equation (2) the estimation model requires defining the expected price, expected cost, and expected yield for each crop in each year. Instead of using futures contract prices, as suggested by other researchers—e.g. Chavas et al (1983) and Holt (1999)—this study uses forecasted prices, yields, and operating costs from a vector autoregression (VAR). The forecasting model used to derive expected crop prices and yields was a two-period lag VAR including time-series data from 1942 to 2013 for the natural logs of

[1] The error terms are assumed to be correlated because total cropland acreage changes very little from year to year. Thus, if the fitted value for acreage of crop *i* is higher than the actual value in year *t*, the fitted value for alternative crop *j* will have to be less than the actual value, unless total agricultural acreage increases within the region.

prices, yields, and acreages for barley, corn, oats, soy, and wheat. The specification of the VAR models is as follows:

$$\mathbf{y_t} = \mathbf{c} + \mathbf{A_1}\mathbf{y_{t-1}} + \mathbf{A_2}\mathbf{y_{t-2}} + \mathbf{u_t}, \tag{3}$$

where $\mathbf{y_t}$ is a *J* by 1 vector of the natural logs of the dependent variables in period t; $\mathbf{c}$ is a vector of constants of the same dimensions; $\mathbf{A_1}$ is a *J* by *J* matrix of time-invariant parameters relating $\mathbf{y_t}$ to its first-order lag ($\mathbf{y_{t-1}}$); $\mathbf{A_2}$ is another *J* by *J*, time-invariant matrix of parameters relating $\mathbf{y_t}$ to its second-order lag ($\mathbf{y_{t-2}}$); and $\mathbf{u_t}$ is a *J* by 1 vector of error terms—each with mean zero and no serial correlation. A separate, second-order VAR was estimated to forecast operating costs for each crop, in which the only variables in $\mathbf{y_t}$ were the natural logs of the operating costs for each crop between 1975 and 2013.

The rationale behind the selection of VAR to determine expected prices, yields, and operating costs is lag structure the model uses: other researchers have used simple first-order lags of crop prices as proxies for expected prices (Houck and Subotnik, 1969; Houck and Ryan, 1972). In addition, with the VAR, the model can be constrained as linear and thus eliminate the concern about functional forms (Pindyck and Rubinfeld, 1997). One may suggest that futures price could have been used instead, however, during the data collection and reporting process, futures contract data for oats was not available.

Since the expected price, cost, and yield variables are forecasts from VAR models, Mean Squared Error (MSE) and Mean Absolute Percentage Deviation (MAPD) for each of the models were calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_t - \hat{y}_t)^2 \tag{4}$$

$$MAPD = \sum_t |y_t - \hat{y}_t| / \sum_t y_t \tag{5}$$

where y_t is the value of the variable (log of cost, price, or yield) for a particular crop in time period t, $\hat{y}_t$ is the forecasted value of the variable for the same crop in time period t, and n is the number of periods in the dataset. Table 1 contains the results of these calculations for the natural logs of yield, price, and cost for each of the five crops. The calculated MSE for each of the forecasted variables appears to be “close to zero” relative to the magnitude of the variables, which indicates a good fit. MAPD indicated the percentage by which the forecasted value of the variable deviates from its actual value on average. For example, the forecasted value of operating cost for oats deviates from its actual value by an average of 0.6%, while the forecasted value of oat price deviates from its actual value by 11%.

Table 1. Mean Squared Error and Mean Absolute Percentage Deviation for Forecasted Yields, Prices, and Costs from the VAR Models

Dependent Variable	MSE	MAPD
FBarleyY	0.022	0.032
FBarleyP	0.005	0.038
FBarleyC	0.005	0.011
FCornY	0.013	0.022
FCornP	0.005	0.034
FCornC	0.003	0.007
FOatY	0.028	0.035
FOatP	0.022	0.110
FOatC	0.002	0.006
FSoyY	0.019	0.035
FSoyP	0.013	0.035
FSoyC	0.003	0.007
FWheatY	0.026	0.041
FWheatP	0.022	0.052
FWheatC	0.006	0.011

Once the expected values for price, cost and yield were obtained, the acreage response function is modelled as:

$$ln(A_{it}) = \beta_{oi} + \sum_{j=1}^{5} \beta_{ij}^{p} \ln{(EP_{jt})} + \sum_{j=1}^{5} \beta_{ij}^{c} \ln{(EC_{jt})} + \sum_{j=1}^{5} \beta_{ij}^{y} \ln{(EY_{jt})} + \varepsilon_{it} \quad (6)$$

where A_{it} is acres for crop *i* at time period *t*; EP_{jt} is the expected price of crop *j* in time period *t*; EC_{jt} is expected cost of crop *j* at time period *t*; EY_{jt} is the expected yield of crop *j* in time period *t*; β_{oi} is the intercept for crop *i*, the β_{ij}^{p} are the own- or cross-price elasticities of acreage response; the β_{ij}^{c} are own- or cross-operating cost elasticities; the β_{ij}^{y} are the own- or cross-yield elasticities; and ε_{it} is an error term for crop *i* in year *t*, with mean zero, variance σ_i^2, $cov(\varepsilon_{it}, \varepsilon_{jt}) = \sigma_{ij}^2$, and $cov(\varepsilon_{(\cdot)t}, \varepsilon_{(\cdot)t-1}) = 0$.

Because the error terms are correlated for this system of equations, seemingly unrelated regression with full information maximum likelihood estimation (SUR) was used in place of ordinary least squares estimation (OLS). The SUR models jointly estimated the elasticity parameters for expected price, expected cost, and expected yield for each of the five crops' acreage response functions.

However, the models showed symptoms of multicollinearity—i.e. high explanatory power but very few statistically significant parameter estimates, often with signs that conflict with economic theory. Because commodity crops are substitutes and/or complements in both production and consumption, it should be no surprise that their prices and costs are highly collinear. Additionally, because crop yields are responsive to weather, yields of all the crops are also highly correlated. The Pearson correlation coefficients and *p*-values were calculated amongst actual prices, yields, and operating costs, and then again for their expected values. More than half of the correlation coefficients between variables, whether for actual values or forecasted values, were discernibly non-zero ($p \leq 0.01$). As a result, it was necessary to remedy the harmful effects of multicollinearity.

Principal Component Analysis (PCA) was applied to reduce these harmful effects. PCA is a powerful statistical procedure that uses an orthogonal transformation to convert all the correlated variables into a new set of linearly uncorrelated variables called "principal components". The principal component scores are generated by the following equation (Jolliffe, 1982):

$$P_{qt} = \sum_{j=1}^{J} a_{jq} Z_{jt} \tag{7}$$

where P_{qt} is the value of principal component *q* in year *t*; a_{jq} is the j^{th} element of the eigenvector for the q^{th} principal component, and Z_{jt} is the standardized value of the natural log of variable *j* in year *t*. Thus, each principal component score is a function of the standardized values of all the original variables. The transformation is defined in such a way that the first principal component (P_1) has the highest eigenvalue—i.e. it explains the largest proportion of the variation in the independent variables. The succeeding principal component explains the next highest proportion of the variation, etcetera. Various criteria are available to determine which principal components should be retained for further investigation. Some studies suggest that sufficient principal components should be retained to explain at least 85% of the variation in the original data (Fekedulegn et al., 2002). However, other research suggests that even principal components with very low eigenvalues may be important in explanatory or predictive principal component regression (PCR) models (Jolliffe, 1982).

Accordingly, we retained all 15 principal components to estimate a seemingly unrelated principal components regression (SU-PCR) by full information maximum likelihood. The model was estimated as follows:

$$ln(A_{it}) = \theta_{oi} + \sum_{q=1}^{15} \theta_{iq} P_{qt} + \omega_{it} \tag{8}$$

where A_{it} is the acreage planted to crop *i* in year *t*; θ_{oi} is the intercept for crop *i*; the θ_{iq} are time-invariant parameters relating the acreage planted to crop *i* to the value of principal component *q*; P_{qt} is the value of principal component score q in year *t*; and ω_{it} is an error term for crop *i* in year *t*, with mean zero, variance σ_i^2, $cov(\omega_{it}, \omega_{jt}) = \sigma_{ij}^2$, and $cov(\omega_{(\cdot)t}, \omega_{(\cdot)t-1}) = 0$.

Based on the results from the estimation of equation (8), principal components were selected for retention. The criterion was to retain any principal component in the equation for crop *i* that had a statistically discernible effect crop i's acreage ($p \leq 0.10$). Symmetry was not imposed across acreage response models for the different crops, so that different sets of principal components could be selected for the various models. After this selection process, the models in equation (8) were re-estimated using only the principal components retained for each acreage response function. The parameter estimates from this equation are not easily interpreted because they describe a relationship between acreage of crop *i* and several principal components, which are functions of the explanatory variables of interest. The invariance property of maximum likelihood estimators means the parameter estimates relating the original explanatory variables to the crop acreages can be obtained by substituting the equivalent linear combinations of the variables in place of the principle components (Johnston, 1972). This is done using the following equations, along with the parameter estimates from equation (8), as follows:

$$\hat{\beta}_{ij}^{(\cdot)} = \sum_q \hat{\theta}_{iq} a_{jq} / s_j \tag{9}$$

$$se\left(\hat{\beta}_{ij}^{(\cdot)}\right) = \sqrt{\sum_q (a_{jq}/s_j)^2 \, var(\hat{\theta}_{iq})} \tag{10}$$

$$\hat{\beta}_{oi} = \hat{\theta}_{oi} - \sum_j \sum_q \hat{\theta}_{iq} a_{jq} \bar{x}_j / s_j \tag{11}$$

$$se(\hat{\beta}_{oi}) = \sqrt{var(\hat{\theta}_{oi}) + \sum_q \sum_j (a_{jq}\bar{x}_j / s_j)^2 var(\hat{\theta}_{iq})} \tag{12}$$

where $\bar{x}_j$ is the mean of the natural log of explanatory variable j, s_j is the standard error of variable j, and all other symbols are as previously defined. The transformed parameters of the SU-PCR are then analyzed based on *t*-tests for individual statistical significance in light of economic theory.

Data

This section describes the sources of the data and how the data is used to design the model. Data required for the model are acreage planted, acreage harvested, crop prices, yield, returns, and costs for barley, corn, oats, soybean, and wheat in North Dakota from 1975 – 2013. Most of the data, except costs and returns, were obtained from QuickStats tool available through the USDA National Agricultural Statistical Service (NASS) website. Due to the difficulty in finding the data for cost and returns for North Dakota, these two data sets were obtained from USDA Economic Research Service for Northern Great Plains. Assumptions were made that Northern Great Plains regional production cost is well correlated with North Dakota's.

The data for prices and costs were all in US dollars; the data for yields was in bushels per acre; and the data for areas planted and harvested were in acres. Since the data for prices and costs were in nominal value, an adjustment was made to convert them to real value. All the prices and cost were deflated using GDP Deflator with base year 2013.

The data for the expected price, expected cost and expected yield that were used in the final model were forecasted using VAR. By positing that price, cost, yield, and acres affect each other inter-temporally, they are all input in the VAR and lagged for 2 years. The forecasted price, yield and cost generated from VAR were then treated as the expected price, yield and cost.

CHAPTER 4. RESULTS AND DISCUSSIONS

This chapter begins by characterizing the data with descriptive statistics, after which estimation results for the crop acreage response functions are presented. Subsequently, fitted values (or in-sample forecasts) and out-of-sample forecasts of acreage for barley, corn, oats, soybeans, and wheat are presented and graphically compared to the actual acreages during the study period.

Table 2 summarizes data used in the study spanning the 1975-2014. Average annual acreage of each crop in North Dakota during the study period was 2.01 million acres of barley, 1.28 million acres of corn, 0.81 million acres of oats, 1.73 million acres of soybeans, and 9.72 million acres of wheat. Wheat acreage has a standard deviation of 1.53 million acres—about 39% of its mean—primarily because the mean has been decreasing since 1995. Barley acreage has a small standard deviation a small standard deviation of 0.79 million acres—again, approximately 39% of its mean—indicating barley acreage in North Dakota has been relatively stable during the past 40 years, despite gradually declining acreage since about 1985. Soybeans acreage has a very large standard deviation due to rapid increases in annual soybeans acreage since 1995. Corn acreage has a large standard deviation due to its mean value consistently trending upward since 1995. Most of the variance of corn acreage about its mean is attributable to this increasing trend. Oat acreage appears to have been trending downward since 1975.

Although corn has a high production cost in the Northern Great Plains Region ($476.23), corn acreage has been increasing rapidly in North Dakota, indicating that corn is gaining comparative advantage in at least some parts of the state through increasing yields and prices. The maximum operating cost for corn in this period was at $631.35 per acre. Table 2 also shows that corn yields are also the highest compared to the yield of other crops. North Dakota corn yield averaged 91.89 bushels per acre, with standard deviation of 25.29—about 28% of its mean—during the past 40 years.

Table 2. Descriptive Statistics for Variables

	Crop				
Variable	Barley	Corn	Oats	Soy	Wheat
Acres	2.01	1.28	0.81	1.73	9.72
(millions)	(0.79)	(0.84)	(0.41)	(1.66)	(1.53)
Yield	50.76	91.89	52.16	27.83	31.94
(bu ac^{-1})	(9.73)	(25.29)	(11.49)	(5.86)	(7.10)
Price	3.94	4.11	2.44	10.53	6.35
($ bu^{-1})	(1.55)	(1.57)	(0.87)	(4.02)	(2.22)
Cost	242.19	476.23	245.21	334.38	278.70
($ ac^{-1})	(39.71)	(89.19)	(30.84)	(72.52)	(54.20)

Note:

1) Price and cost are given in 2013 $USD.
2) Numbers in parentheses are standard deviations.

Results from SUR crop acreage models from full information MLE

Table 3 presents the parameter estimates of the SUR crop acreage response models from full information MLE as described in equation (6). Because few of the parameter estimates are statistically significant—eight or fewer of the 15 estimates in each model—it appears the models would not have high overall explanatory power. For example, in the barley acreage response model in 3, only expected barley cost and expected corn yield have discernible impacts at the 1% significance level, while expected barley yield has a discernible impact only at the 5% level and expected oat cost and soybeans yield are statistically significant only at the 10% level. However, the low mean squared error (MSE) indicates high explanatory power. Corn acreage response model has six variables with discernible impacts at the 10% significance level or better; however, the own-price elasticity of corn acreage response is negative—contrary to expectations of economic theory—and is significant (10% level).

Table 3. Seemingly Unrelated Regression Crop Acreage Response Models from Full Information Maximum Likelihood Estimation

	Acreage Response Models				
Parameter	Barley	Corn	Oats	Soybeans	Wheat
Intercept	27.05***	9.25***	20.05***	11.51**	20.20***
	(2.97)	(2.69)	(3.12)	(4.41)	(1.21)
FBarleyY	2.32**	-0.41	-0.04	-2.28	0.66
	(1.03)	(0.93)	(1.08)	(1.53)	(0.42)
FBarleyP	-0.15	1.15***	-1.11**	1.24*	0.47**
	(0.44)	(0.39)	(0.46)	(0.65)	(0.17)
FBarleyC	-2.56***	0.29	-1.74**	3.13***	0.22
	(0.66)	(0.59)	(0.69)	(0.98)	(0.27)
FCornY	-1.64***	0.22	-0.12	1.07*	-0.70***
	(0.41)	(0.37)	(0.43)	(0s.60)	(0.17)
FCornP	0.69	-0.96*	1.52**	-0.93	-0.33
	(0.60)	(0.54)	(0.63)	(0.89)	(0.25)
FCornC	-0.78	-0.98	1.32	-2.57	-0.78*
	(1.08)	(0.98)	(1.13)	(1.60)	(0.44)
FOatY	-0.94	0.14	-0.02	0.17	0.09
	(0.68)	(0.62)	(0.72)	(1.01)	(0.28)
FOatP	0.13	0.77**	-0.07	0.58	-0.38**
	(0.33)	(0.30)	(0.35)	(0.49)	(0.14)
FOatC	1.28*	2.87***	-0.99	2.83***	-0.27
	(0.61)	(0.55)	(0.64)	(0.90)	(0.25)
FSoyY	1.29*	0.20	-0.05	-0.36	0.17
	(0.58)	(0.52)	(0.61)	(0.86)	(0.24)
FSoyP	0.37	-0.30	1.04**	-1.38**	-0.41**
	(0.39)	(0.35)	(0.41)	(0.58)	(0.16)
FSoyC	-1.41	0.288	-2.01**	0.01	0.66*
	(0.85)	(0.77)	(0.89)	(1.26)	(0.35)
FWheatY	-0.69	1.47***	-1.05*	2.45***	-0.71***
	(0.49)	(0.44)	(0.51)	(0.72)	(0.20)
FWheatP	-0.47	0.59	-2.04***	0.71	0.55***
	(0.40)	(0.37)	(0.43)	(0.60)	(0.17)
FWheatC	1.18	-2.70***	3.07***	-3.09***	-0.12
	(0.74)	(0.67)	(0.78)	(1.11)	(0.30)
MSE	0.047	0.039	0.052	0.105	0.008

Note: [1] Standard errors are in parentheses below the parameters estimate
[2] Natural logarithmic form
[3] Description of the variables is in Appendix 1
* statistical significance at 10 percent level
** statistical significance at 5 percent level
*** statistical significance at 1 percent level

Additionally, the cross-price elasticities of barley and oats in the corn acreage response function have unexpected signs and are significant at the 1% and 5% levels, respectively. In fact, the acreage response functions for all crops show relatively few statistically significant parameters, some of which have signs inconsistent with economic theory, but jointly high explanatory power. These are classic symptoms of multicollinearity—that is, highly correlated explanatory variables have inflated the estimated standard errors, reducing the validity of statistical inferences from this model.

Tests of the strength and direction of the linear relationships between the explanatory variables were then performed using Pearson Correlation coefficients. The 105 Pearson Correlation coefficients are not presented in tabular form. Suffice it to say that 71 of the coefficients were strongly significant ($p < 0.01$), another 17 were moderately significant ($0.01 < p < 0.05$), and a further 5 were marginally significant ($0.05 < p < 0.10$). All the cross-price correlations, for example, were greater than 0.75 and significant ($p < 0.01$). All cross-yield correlations also were greater than 0.45 and significant ($p < 0.01$). This is strong evidence that multicollinearity is making the SUR acreage response functions from equation (6) unreliable for statistical inference.

Results from acreage models with PCA

In order to remedy high multicollinearity in the previous models, principal components are generated using equation (7). The principal components with discernible impacts ($p \leq 0.10$) are then used to estimate acreage response functions for each crop as described in equation (8), and are then finally transformed into parameters relating the original independent variables to the acreage responses using equations (9) through (12). These transformed parameter estimates and their standard errors are presented in Table 4 for each crop acreage response function. The acreage response models each have high explanatory power, as indicated by the low MSE and

MAPD scores. Additionally, more parameter estimates are statistically significant after correcting for multicollinearity compared to the uncorrected model.

Barley

Based on table 4, the estimated acreage response model explains the historical variation in barley acreage well. Twelve of the fifteen parameter estimates are statistically significant at the 10% level or better, and parameter estimates for expected barley, corn, and oat yields have the signs hypothesized by economic theory. Notably, expected commodity prices do not appear to play as large a role in barley allocation decisions as expected production yield and expected cost for each crop. For example, the estimates indicate that a 1% increase in expected barley yield will increase barley acreage by 1%, while a 1% increase in expected corn yield will decrease barley acreage by 2.02%. In addition, a 1% increase in oats expected yield will decrease barley acreage by 0.62% (5% significant level). In effect, if the expected yield of the three crops is expected to increase by 1%, barley acreage should decrease by approximately 1.64%. The signs of these coefficients are consistent with economic theory.

Besides yield, expected costs of own and barley's competing crops also play significant effect on its acreage. Among all the cost elasticities, barley's expected cost and oats expected costs are statistically significant (at 1% level) for barley acreage model. The coefficients for barley's expected cost and oats expected costs are -1.79 and 1.52 respectively. These results suggest that there will be a decrease of barley's acreage by 1.79% if barley's production is increased by 1% and at the same time there would be an increase of barley acreage by 1.52 if oats expected cost is increased by 1%. In effect, if the expected cost of both barley and oats increase 1%, barley acreage should decrease by approximately 0.27%. The cost would mostly come from seeds and other input costs such as fertilizers used in planting. The increase in cost would eventually reduce the acres provided for barley. Expected corn cost is also statistically significant at 1% level, however, the coefficient sign is not as expected. Expected wheat cost is not statistically significant to affect barley acreage.

While expected yield and costs of the crops to some extent affect greatly farmers' decision for barley acreage, expected price variables do not lend the same effect. All of the price elasticities, except for barley's and oats' expected price, do not have statistical significance effect on barley acreage. The coefficient of barley's and oats expected price is 0.43 and -0.36 (both at 1% level), indicating that if both crops expected price increase by 1%, the land allocated for barley will be increased by 0.07% only. Although the result of the oats price elasticity with regards to barley acreage is small, it explains the substitutability of barley and oats in production. The increase in oats price compared to barley would relatively induce farmer to move away from barley and plant more of oats instead. Other price variables such as expected price for corn and soybeans are also significant at 1%, however the coefficient signs for these two variables do not conform to the theory of cross price elasticity.

Compared to the elasticities of other crops, wheat's expected yield, price and cost are not statistically significant to affect barley acreage. Soybeans expected price yield and costs are significant at 1% level, however, the coefficient signs of both do not conform to the conventional economic wisdom. The results suggest that a 1% increase in soybeans yield will increase barley's acreage by 1.36% while a 1% increase in soybeans costs will reduce barley's acreage by 0.91%. A plausible explanation for these results could be that soybeans and barley are complement in production. In some part of the state some farmers plant barley and soybeans in rotation. Hence, soybeans' expected cost and yield have contradicting signs.

Table 4. Seemingly Unrelated Principal Components Regression Estimates of Crop Acreage Response Functions

	Acreage Response Models				
Parameter	Barley	Corn	Oats	Soybeans	Wheat
Intercept	29.46***	6.53**	25.62***	6.36*	20.29***
	(2.48)	(2.40)	(2.36)	(3.28)	(0.98)
FBarleyY	1.00***	0.41***	-2.40***	-0.19	0.66**
	(0.33)	(0.08)	(0.61)	(0.31)	(0.25)
FBarleyP	0.43***	0.43***	-0.30	0.51***	0.55***
	(0.11)	(0.10)	(0.30)	(0.08)	(0.13)
FBarleyC	-1.79***	0.87***	-1.07***	3.21***	-0.00
	(0.18)	(0.18)	(0.22)	(0.39)	(0.15)
FCornY	-2.02***	0.39	-0.66***	1.65***	-0.82***
	(0.32)	(0.27)	(0.09)	(0.13)	(0.10)
FCornP	0.30***	0.22***	0.93**	0.25	-0.63***
	(0.08)	(0.08)	(0.42)	(0.15)	(0.18)
FCornC	-1.48***	-0.38**	0.31	-3.17***	-0.20*
	(0.36)	(0.17)	(0.19)	(0.71)	(0.11)
FOatY	-0.62**	-0.79***	1.01**	-1.29***	0.22
	(0.23)	(0.18)	(0.44)	(0.22)	(0.19)
FOatP	-0.36***	0.20***	-0.23*	0.17*	-0.26***
	(0.12)	(0.07)	(0.12)	(0.10)	(0.07)
FOatC	1.52***	1.80***	-0.22	1.45**	-0.07
	(0.43)	(0.42)	(0.34)	(0.57)	(0.22)
FSoyY	1.36***	0.78**	-0.21	0.47*	0.04
	(0.42)	(0.32)	(0.22)	(0.22)	(0.14)
FSoyP	0.14	0.05	0.03	-0.51***	-0.36***
	(0.23)	(0.14)	(0.13)	(0.17)	(0.09)
FSoyC	-0.91***	-0.85***	-0.85**	0.17	0.15
	(0.19)	(0.13)	(0.33)	(0.51)	(0.15)
FWheatY	-0.14	0.78***	-0.01	1.39***	-0.62***
	(0.14)	(0.13)	(0.13)	(0.17)***	(0.10)
FWheatP	-0.18	-0.07	-1.17***	-0.43***	0.69***
	(0.19)	(0.09)	(0.23)	(0.12)	(0.11)
FWheatC	0.65	-1.16***	1.47***	-1.18***	-0.22
	(0.50)	(0.30)	(0.32)	(0.23)	(0.18)
MSE	0.034	0.031	0.046	0.090	0.006
MAPD	0.145	0.171	0.178	0.246	0.061

Note: [1] Standard errors are in parentheses below the parameters estimate
[2] Natural logarithmic form
[3] Description of the variables
* statistical significance at 10 percent level
** statistical significance at 5 percent level
*** statistical significance at 1 percent level

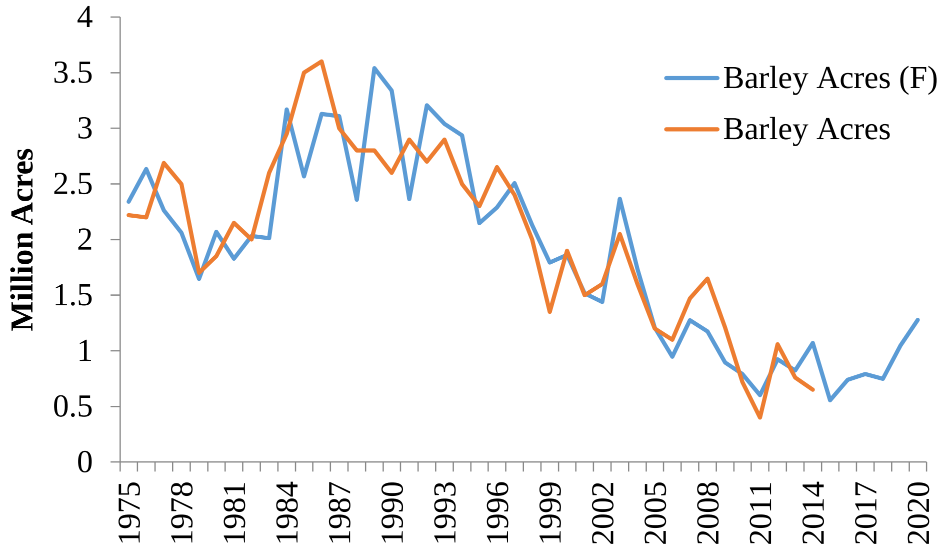

Figure 2. Barley's Acreage Forecast

Overall, it is concluded that farmers' decisions for barley acreage allocation are mostly dependent on the expected yields of barley, corn, and oats. Expected costs of own- and competing crops plays little role in the barley acreage model. Moreover, price factors have almost no effect on barley acreage, with only expected price of barley and oats total effect of 0.08%.

Figure 2 shows the fitted values (or in-sample forecasts) and out-of-sample forecasts of acreage for barley. Any change in the expected yield of corn and oats in the short term will affect the acreage for barley to decline. However, by 2020 barley acreage is expected to slowly increase by 98% to that of in 2014.

Corn

In contrast to barley acreage model, corn acreage model is significantly affected by cost factors, especially barley's expected costs and oats expected cost. The parameter estimate of barley's and oats' expected cost are 0.87 and 1.80 respectively (1% significant level), indicating that a 1% increase in barley and oats expected price would increase corn acreage by 0.87% and 1.80%, making a total of 2.67 % acreage change if both costs increase by 1% at the same time. Soybeans and wheat's expected costs are also significant at 1% level with parameter estimate of -0.85 and -1.16 respectively. Due to the negative coefficient signs, both results may be interpreted as irrelevant in corn acreage decision. However, due to complementary relationship in production between corn and soybean, and corn and wheat in some part of the state, such elasticities may exist. The result suggests that a 1% increase in soybeans and wheat expected costs would reduce corn acreage by 0.85% and 1.16% respectively. Corns' own expected cost is significant at 5% level and coefficient indicating that its own expected costs do not have significant effect on its acreage.

While cost elasticities have significant effect on corn acreage, price elasticities have almost no effect on corn acreage model. Of all the price variables, only expected corn is significant at 1%. In addition, the coefficient of corn expected price is also relatively small, indicating that a 1% increase in corn expected price will increase corn acreage by 0.22%.

Worth emphasizing also that the coefficients of expected yield and costs for both soybeans and wheat are in contrary to the economic theory. Nevertheless, the results reflect the average farming practice and acreage response throughout the state where soybeans and corn, and wheat and corn are planted in rotation. The complementarity of these crops may have contributed to the incorrect signs on each of the coefficient.

Apart from expected soybeans and wheat yield, oats yield is also significant to corn acreage. The estimation results show that a 1 % increase in oats expected yield would decrease corn acreage by 0.79%. Corns' and barley's expected yield do not have significant effect on corn acreage.

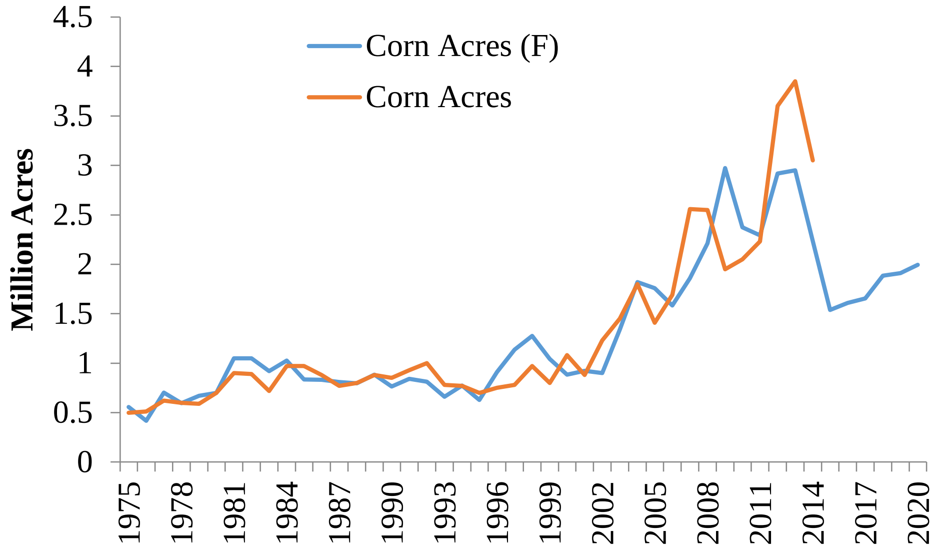

Figure 3. Corns' Acreage Forecast

Overall, corn's own expected yield does not affect its acreage. Farmers' decision for corn acreage is significantly affected by barley's expected costs, oats expected cost, wheat's and soybean's expected yield, and corns' expected price and cost. Figure 3 shows the in-sample forecasts and out-of-sample forecasts of acreage for corn. With the increasing yield of wheat and soybean, coupled with increasing soybeans price in the years to come, corn acreage is estimated to decline rapidly until 2016. Although it is expected to increase by 2020, it may only gain a third of the acreage lost since 2014.

Oats

Table 4 column 4 depicts the parameter estimation for oats acreage model. Being as traditional small grains that occupy the least of the land in North Dakota, oats' acreage is mostly affected by other competing crops' expected cost, yield and price. As shown in the oats model (Table 4), oats acreage is generally affected by barley's expected yield, wheat's expected price, and wheat's expected cost. Barley's expected yield, wheat' expected price and wheat's expected cost have higher coefficient at -2.40, -1.17, and 1.47 respectively (all at 1% level), indicating that these variables have stronger effect in farmers decision for oats acreage allocation. If these three parameters are expected to increase by 1%, the total effect is a 2.1% reduction in oats acreage.

Barley's expected costs and soybeans expected costs are statistically significant at 1% and 5% level respectively. However the coefficient signs are not as expected. They do not explain well the elasticities of expected price of barley and soybeans with respect to oats acreage. Oats own expected cost and corns' expected costs are not statistically significant to affect its acreage.

With regards to cross yield elasticities, corns' and oats own expected yield also affect oats acreage, beside barley yield as previously mentioned. Corns' expected yield and oats expected yield are statistically significant at 1% and 5% level respectively. The coefficients for both parameters are -0.66 and 1.01 respectively, indicating that a 1% increase in corn yield will reduce oats acreage by 0.66%, while a 1% increase of oats yield will increase oats acreage by 1.01%. In effect, if the expected yield of barley, corn and oats is expected to increase by 1%, oats acreage should decrease by approximately 2.05%. The signs of these coefficients are consistent with economic theory.

Price elasticities have little effect on oats acreage. Most of the expected price parameters, except wheat's expected cost, are not statistically significant. Oats own expected price is significant at 10% level, and corns expected price is significant at 5% level, however, the coefficient signs for both are in contrary to economic theory. The plausible explanation for this is that oats selling price is the lowest compared to the other four crops included in this study (Table 2), and that corn is not substitute in production with oats.

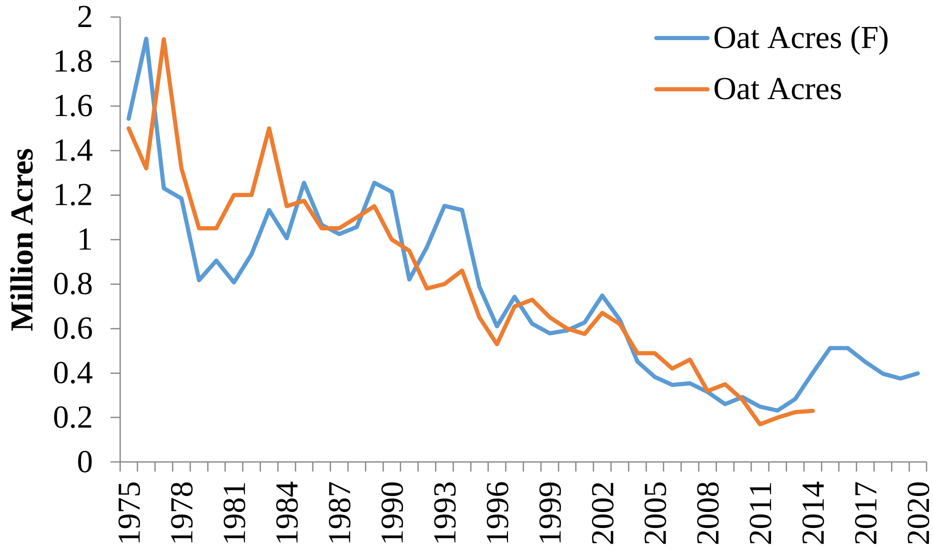

Figure 4. Oats' Acreage Forecast

Overall, oats acreage model indicates that yield, price and cost of other crops have greater effect on oats acreage, while oats own price, costs, and yield have less effect on acreage allocation. Although high coefficient of expected barley yield along with increasing wheat price may suggest a decreasing trend of oats in the future, Figure 6 shows that the increase in wheat's expected cost and oats own expected yield may offset further decrease. It is estimated that oats acreage will slightly increase to almost 0.4 million acres by 2020 (Figure 4).

Soybean

Similar to those other results for other crops, the primary factor that affect soybeans acres is the expected cost of other crops. As shown in the soybeans model, expected barley cost and expected oats costs have high significant effect on soybeans acreage at 1% level. The coefficients are 3.21 and 1.45 for expected barley cost and expected oats respectively, indicating that a 1% increase in both expected barley and oats cost, would result in a 4.65% increase in soybeans acreage. The expected cost of corn and wheat also show significant effect (1% level) on soybeans acreage, however the coefficient sings for both do not conform to the economic theory. For soybean's expected cost, this occurs due to the complementarity relationship between soybeans and corn. Most farmers plant corn and soybeans and corn in rotation.

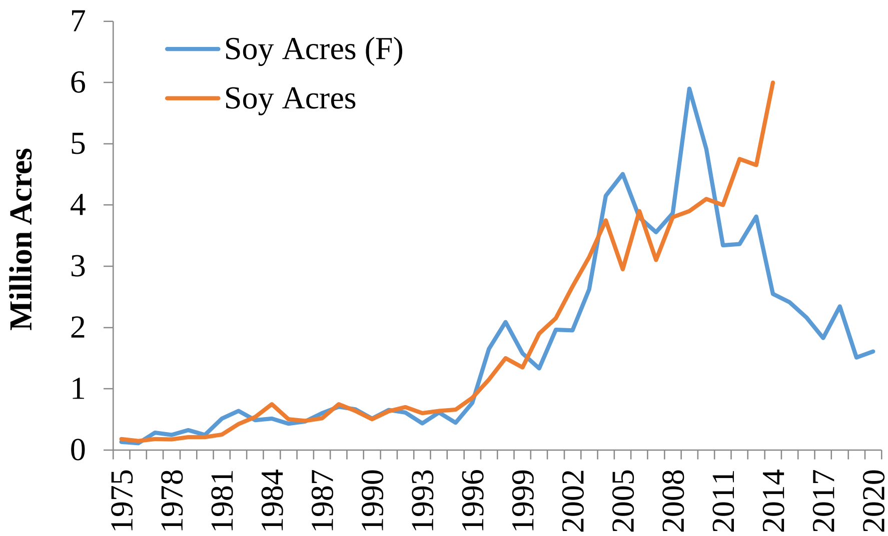

Figure 5. Soybeans' Acreage Forecast

While costs factors affect greatly soybeans acreage, price variables in the model do not have much significant effect on soybeans acres. Corn, having being substitute and complement to soybean, its expected price has no significant effect on soybeans acres. Surprisingly, the coefficient sign of soybeans' own expected price is also negative, despite the fact that soybean's average selling price is the highest (at an average of $11.53) among the five crops studied (Table 2). The incorrect signs of the coefficient are also seen on barley's expected price, oats' expected price, corns expected yield, and wheat's expected yield. These results may reflect the complementarity of soybeans with barley and wheat as well as substitutability of oats and barley in production.

With regards to yield, it is noted that expected oats yield has statistically significant effect on soybeans yield at 1% level. The coefficient explains that a 1% increase in oats expected yield will reduce soybeans acreage by 1.29%. In addition, soybean's own expected yield is also significant at 10% level with its coefficient 0.47. In effect, if the expected yield of both oats and soybeans is expected to increase by 1%, soybeans acreage should decrease by approximately 0.82%.

Overall, with the constant increasing of soybeans' and wheat's price; and corn's cost of production, soybeans acreage is expected to decrease in years to come. Figure 5 shows soybeans' forecasted acres to 2020. Soybeans acreage is expected to drop significantly down to 1.6 million acres despite its high price in this study period.

Wheat

In contrast to the other four crops, wheat acreage model is not dependent on its own- and competing crops' expected costs. All the costs variables, except expected cost for corns, are not statistically significant with regards to wheat acreage. Even though corns' expected cost is statistically significant (at 5% level), its coefficient sign is not as expected. As explained earlier, this could be because some farmers in the state plant wheat and corn in rotation. Nevertheless, the effect is relatively small, indicating that a 1% increase of corns' expected costs will reduce wheat's acreage by 0.20%.

In regards to elasticities of prices, the expected prices of all crops, except for barley are statistically significant. Corns' expected price, oats expected price, soybeans expected price and wheat's expected price are all statistically significant at 1% with parameter coefficients -0.63, -0.26, -0.36 and 0.69 respectively. In effect, if the expected price of these crops is expected to increase by 1%, wheat acreage should decrease by approximately 0.56%.

Among all the parameters, corns' expected yield has the highest effect on wheat acreage. Expected corn yield is statistically significant at 1% level with its elasticity parameter -0.82, indicating that a 1% increase in corns' expected yield will decrease wheat acreage by 0.82%. While corns expected yield has significant effect on wheat acreage, wheat's own expected yield does not lend the same effect. Although its coefficient is shown as significant at 1% level, the sign is not as expected. The expected wheat yield coefficient suggests that a 1% increase in wheat yield would reduce wheat acreage by 0.62%. In addition to wheat yield, expected barley yield and barley price also do not show the correct signs. This may be contributed by the fact that prices and yield of barley and wheat are highly correlated.

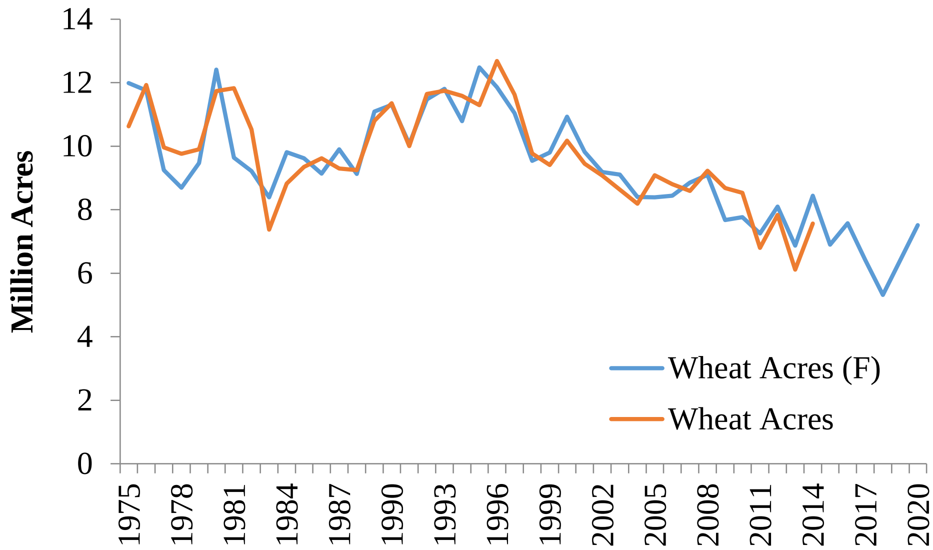

Figure 6. Wheat's Acreage Forecast

To conclude, expected yield of corn and expected price of corns, oats, soybeans and wheat have significant effect on wheat acreage. The expected costs of wheat own- and the competing crops are not statistically significant affecting wheat acreage decision. Figure 6 shows the forecasting model of wheat up to 2020. While yield of other crops may induce farmers to shift their crop allocation away from wheat, wheat's own yield steady yield provide incentive and offset the decrease. A slight decrease may be expected to incur by 2018 however, wheat acreage is expected to rise again by 2020.

CHAPTER 5. SUMMARY AND CONCLUSIONS

The change in agricultural and energy policy, together with increasing export demand from developing countries such as China have affected crops prices in North Dakota in the last two decades. The continuous change of prices and other economic factors such as input costs and technology, has affected land use in much of North Dakota. Crops that previously were not economically viable in much of North Dakota, especially corn and soybeans, have become competitive with the traditional small grains agriculture of the state, gaining a higher share of crop acreage.

While increasing price may lend higher revenue for farmers, it may also lead to farming practices that could affect farm profitability, financial stability and environmental health. A proper forecasting model is required to help farmers make their optimal selection facing changes in prices, cost, and other market variables. Hence, the objective of this study was to examine the extent to which farmers' crop allocation decision be affected by price, and the magnitude of price effect on barley, corn, oats, soybeans and wheat acreage.

Forecasting models for barley, corn, oats, soybean, and wheat were developed using seemingly unrelated principal components regression by full information maximum likelihood. The explanatory variables were expected prices, costs, and yields. Data were collected from USDA NASS and USDA ERS database.

Results

The results of the study showed that farmers' decision for acreage allocation is varied across the crops depending on how responsive they are to price, cost and yield of its own and competing crops'. It is also revealed that the substitutability or complementarity of crops in the production has positive effect on crops selection when facing price, cost and yield changes.

In contrast to previous findings (Chembezi and Womack, 1992; Weersink et al, 2010), this study found that prices have little effect on acreage response compared to costs and yield variables in most of the crop models. The distribution of lands to different crops is expected to be affected by the cost and yield of competing crops. For example, barley's acreage response is found to be affected mostly by the expected yield of barley, corn, and oats. Expected costs of own- and competing crops plays little support in barley model. Price factors have almost no effect on barley acreage. The finding from barley model also revealed how soybeans' expected yield and cost affect barley's acreage if these two crops are to be planted in rotation. The complementarity relationship these two crops also affect how one crop's expected cost will affect the other crop's acreage.

Since barley's model is partially affected by the expected yield of oats and corns, it is no surprise that oats acreage model also depicts its dependency on barley's and corns' expected yield. An increase in barleys' and corns' expected yield along with the increase in expected wheat price is estimated to reduce oats acreage substantially. Fortunately, as oats own expected yield is expected to increase in the next five years along with the increase in wheat's expected costs, the reduction would not be as big. In fact, the model suggested that oats acreage will slightly increase in the next five years.

While barley acreage may have been contributed by the expected yield of corn, corn acreage—on the other hand—is not influenced by the expected yield of barley. Farmers' decision for corn acreage is primarily affected by barley's expected costs and oats expected cost. It is no surprise that the expected costs of these crops are well correlated due to the fact that they require the same fertilizer in production. In addition, the cost effect seems to have more effect because crop farmers have sufficient information of the operating costs at planting time than they do about the expected prices of these crops. The relative certainty about production costs at planting time gives cost variables higher weight in the farmer's decision in corn model.

It is surprising that corn yield do not lend much effect on corn acreage. Instead, corn acreage in part is affected positively by the expected soybeans yield and wheat yield; and negatively by the expected oats yield. Since soybeans and corn, and soybean and wheat are complementary in production in some part of the state, an increase in production of soybeans or wheat will induce farmers to plant more of corns on the same field on the following year.

Wheat's acreage model appears to support Krause and Koo's (1997), and Chembezi and Womack's (1992) findings that price and yield do contribute to wheat acreage. In addition to its own price, prices of other competing crops also affect farmer's decision for wheat acreage. In contrast to other crops studied, wheat's own- and competing crops are not statistically significant to affect wheat acreage. The increase in corns expected yield, oats expected price, and soybeans' expected price may induce farmers to shift their crop allocation away from wheat in the next few years however, steady yield of wheat in the long run may bring back the acres of land for wheat to the level it is today in 2020.

Future study

There is a need to include weather as one of the variables in acreage modeling. Given the role of weather in crops yield production, the inclusion of weather could better explain the variance of yield and thus provide robust results. Different climatic conditions, the intensity of the weather are some that is believed to be useful in future research.

One other factor that needs to be taken into account in further research is risk factors, especially price risk. Recent developments have signaled that financial markets affect North

Dakotan farmers’ acreage allocation. An inclusion of risk in crop modeling would provide robust results.

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APPENDIX A. LIST OF VARIABLES

Variables		Description
BarleyA	=	Barley Acres
CornA	=	Corn Acres
OatA	=	Oats Acres
SoyA	=	SoybeansAcres
WheatA	=	Wheat acres
FBarleyY	=	Forecasted Barley Yield
FBarleyP	=	Forecasted Barley Price
FBarleyC	=	Forecasted Barley Cost
FCornY	=	Forecasted Corn Yield
FCornP	=	Forecasted Corn Price
FCornC	=	Forecasted Corn Cost
FOatY	=	Forecasted Oats Yield
FOatP	=	Forecasted Oats Price
FOatC	=	Forecasted Oats Cost
FSoyY	=	Forecasted Soy Yield
FSoyP	=	Forecasted Soy Price
FSoyC	=	Forecasted Soy Cost
FWheatY	=	Forecasted Wheat Yield
FWheatP	=	Forecasted Wheat Price
FWheatC	=	Forecasted Wheat Cost

APPENDIX B. EIGENVECTORS OF THE PRINCIPAL COMPONENTS

	Eigenvectors for the Principal Components														
Variable	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7	Prin8	Prin9	Prin10	Prin11	Prin12	Prin13	Prin14	Prin15
FBarleyY	-0.10	0.369	-0.193	0.007	0.071	-0.100	-0.031	0.080	0.090	-0.139	0.119	0.239	-0.320	0.676	0.370
FBarleyP	0.44	0.246	-0.168	-0.504	-0.437	0.190	-0.167	-0.088	-0.176	-0.153	-0.129	0.172	0.280	0.108	-0.104
FBarleyC	0.07	0.356	0.213	0.185	-0.231	-0.159	0.009	-0.357	0.067	-0.499	0.208	-0.366	-0.291	-0.108	-0.233
FCornY	-0.19	0.464	0.389	-0.155	-0.151	0.327	0.244	0.229	0.081	0.371	0.404	-0.061	0.121	-0.060	0.021
FCornP	0.45	0.127	-0.299	-0.177	0.229	0.092	0.068	0.405	0.403	0.026	-0.036	-0.231	-0.365	-0.272	-0.001
FCornC	0.19	0.075	-0.095	0.325	-0.161	0.084	0.020	0.059	-0.294	-0.028	-0.039	-0.381	0.204	-0.138	0.713
FOatY	-0.11	0.364	-0.367	0.186	0.404	-0.090	-0.208	0.138	-0.083	-0.215	0.289	0.088	0.486	-0.180	-0.199
FOatP	0.33	0.102	0.475	0.058	-0.018	-0.653	-0.044	0.398	-0.065	0.022	-0.083	0.199	0.112	-0.013	0.015
FOatC	0.09	0.051	-0.069	0.410	-0.259	0.016	0.085	-0.102	0.697	0.110	-0.211	0.032	0.387	0.181	-0.062
FSoyY	-0.1	0.294	0.211	0.262	0.063	0.406	-0.038	0.181	-0.099	-0.247	-0.581	0.315	-0.165	-0.201	-0.034
FSoyP	0.379	0.018	0.076	0.035	0.373	0.084	0.682	-0.353	-0.091	-0.088	0.075	0.283	0.092	0.006	0.060
FSoyC	0.233	-0.05	-0.152	0.423	-0.124	0.156	0.145	0.282	-0.399	0.193	0.058	-0.153	-0.116	0.369	-0.477
FWheatY	-0.07	0.450	-0.222	-0.031	0.062	-0.321	0.041	-0.349	-0.159	0.555	-0.368	-0.107	-0.116	-0.110	-0.071
LFWheatP	0.32	0.036	0.371	0.057	0.440	0.266	-0.546	-0.258	0.044	0.198	0.016	-0.160	0.034	0.232	0.010
LFWheatC	0.19	-0.03	-0.120	0.303	-0.251	0.045	-0.260	-0.159	0.005	0.240	0.378	0.537	-0.287	-0.340	0.088

APPENDIX C. ACREAGE RESPONSE AS FUNCTION OF PRINCIPAL COMPONENTS

	Acreage Response Models				
Parameter	Barley (9)	Corn (10)	Oats (11)	Soybeans (12)	Wheat (13)
Intercept	14.43***	13.90***	13.45***	13.83***	16.08***
	(0.03)	(0.03)	(0.03)	(0.05)	(0.01)
Prin1	-	-0.10***	0.18***	-0.68***	-
		(0.04)	(0.03)	(0.04)	
Prin2	-0.99***	1.23***	-1.28***	2.14***	-0.29***
	(0.08)	(0.09)	(0.10)	(0.13)	(0.03)
Prin3	-1.07***	0.72***	-1.28***	1.76***	-0.17***
	(0.14)	(0.16)	(0.18)	(0.23)	(0.06)
Prin4	-	-	-	-0.85***	-
				(0.11)	
Prin5	0.45**	-	-	-0.95***	-
	(0.18)			(0.16)	
Prin6	-	-0.71**	-	-	0.39***
		(0.28)			(0.12)
Prin7	-	-	0.95***	-1.35***	-
			(0.24)	(0.33)	
Prin8	-	-	-	-1.20***	-
				(0.29)	
Prin9	1.77***	1.39***	-	1.79***	-
	(0.42)	(0.47)		0.39)	
Prin10	-	-	-	-	-0.66***
					(0.15)
Prin11	-1.99***	-1.40**	-	-	-
	(0.52)	(0.57)			
Prin12	2.22***	-	-	-	-
	(0.67)				
Prin14	-	-	-2.96***	-	1.03**
			(0.86)		(0.38)
Prin15	-	-	-	-3.39***	-
				(0.99)	
MSE	0.04	0.05	0.06	0.11	0.01